

FINAL REPORT

Title: Modeling the Influence of Climate and
Local Site Factors on Post-Fire Regeneration in
the Southern Rocky Mountains

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KEYWORDS

Wildfire, Seed Production, Seedling Establishment, Dry Forests, Regeneration, Conifer, Ponderosa Pine, Douglas-fir, Climate Filtering, Fire Severity

LIST OF ABBREVIATIONS AND DEFINITIONS

- AET – Annual actual evapotranspiration (summed for all months in a calendar year). AET is the total amount of evapotranspiration constrained by the availability of soil moisture; a proxy for site productivity. Quantified using equations in Lutz et al. (2010) and Dobrowski et al. (2013).
- AIC – Akaike information criterion. A measure of the relative quality of competing statistical models.
- BA – Total stand basal area (in $\text{m}^2 \text{ha}^{-1}$).
- BRT – Boosted regression tree model. A non-parametric statistical technique used for classification and regression.
- CWD – Annual climatic water deficit (summed for all months in a calendar year). CWD is the unmet evaporative demand of the atmosphere (i.e., potential evapotranspiration [PET] - AET); a proxy for drought stress. Quantified using equations in Lutz et al. (2010) and Dobrowski et al. (2013).
- DBH – Tree diameter at breast height (1.37 m above ground level).
- GLMM – Generalized linear mixed model. A regression technique that allows for analyses including both random effects and non-normal response variables.
- gridMET – Gridded meteorological dataset of Abatzoglou (2013)
- HLI – Heat load index. A relative measure of solar heating on a site that combines slope, aspect, and latitude (McCune and Keon 2002).
- MTBS – The Monitoring Trends in Burn Severity database (Eidenshink et al. 2007)
- ρ – Spearman's rank correlation coefficient
- PRISM – Gridded climate dataset Parameter-elevation Regressions on Independent Slopes Model (PRISM 2018).
- NAIP – National Agriculture Imagery Program (USFS 2015)
- SRME – Southern Rocky Mountains Ecoregion. EPA Level III Ecoregion 21.
- TPI – Topographic position index. The difference between the elevation of a site and the mean elevation of the surrounding area (Weiss 2001).

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ABSTRACT

Climate warming is contributing to increases in wildfire activity throughout the western U.S., leading to potentially long-lasting shifts in vegetation. The response of forest ecosystems to wildfire is thus a crucial indicator of future vegetation trajectories, and these responses are contingent upon factors such as seed availability, interannual climate variability, average climate, and other components of the physical environment. To better understand variation in resilience to wildfire across vulnerable dry forests, we surveyed conifer seedling densities in 15 recent (1988-2010) wildfires, developed generalized linear mixed models to predict seedling density based on biophysical factors, and predicted post-fire seedling densities at a 30-m resolution within each fire perimeter. For spatially-explicit predictions, we used a combination of downscaled climate data, monthly water balance models, and maps of surviving forest cover. Ponderosa pine and Douglas-fir (*Pseudotsuga menziesii*) seedling densities were higher on more mesic sites and adjacent to surviving trees, though there were also important interspecific differences, likely attributable to drought- and shade-tolerance. We estimated that post-fire seedling densities in 42% (for ponderosa pine) and 69% (for Douglas-fir) of the total burned area were below the lowest reported historical tree densities in these forests.

We also characterized temporal variation in conifer seedling establishment and quantified the relationship between establishment and interannual climate variability using destructively-sampled seedlings and gridded climate data. We then combined the new field data collection of 302 ponderosa pine and Douglas-fir seedlings with previously collected samples in the Colorado Front Range. Using these data, we developed boosted regression tree models to predict seedling establishment in each year as a function of annual climatic water deficit, annual actual evapotranspiration, total growing season (i.e., April-September) precipitation, and time since fire occurrence. At the site-level, Douglas-fir and ponderosa pine seedling establishment was most abundant between 1-10 years post-fire, and in years with high growing season precipitation and high actual evapotranspiration.

Our findings indicate that post-fire recovery of dry coniferous forests is a complex process in both space and time. For non-serotinous, obligate seeding conifers, the greatest post-fire seedling densities can be expected in close proximity to seed trees. However, some sites show low seedling densities even with the presence of surviving overstory trees because of low moisture availability. Local vegetation cover, the timing of seed production, non-linear impacts of fire severity, and interannual climate variability also have important influences on post-fire forest recovery. When post-fire artificial regeneration is deemed necessary in dry forests, it should be prioritized on wetter sites and far from surviving trees, ideally taking place in years with abundant moisture availability. These types of sites – that are climatically suitable but distant from seed trees – can be easily identified using publicly available spatial datasets, better informing post-fire management strategies.

1. PROJECT OBJECTIVES

*1) Survey post-fire conifer establishment and densities of re-sprouting species in 5-8 fires, focusing primarily on forests dominated by ponderosa pine (*Pinus ponderosa* var. *scopulorum* (Engelm.)), Douglas-fir (*Pseudotsuga menziesii* var. *glauca* (Mayr) Franco), and/or Gambel oak (*Quercus gambelii* Nutt).*

Completed. The graduate student investigator used funding from the Joint Fire Science Program's Graduate Research Innovation Award to partially support field data collection in 555 post-fire regeneration plots spanning 15 recent wildfires in the specified vegetation types (i.e., ponderosa pine, pine-oak, and dry mixed-conifer), greatly exceeding the original project goal. All surveyed wildfires occurred in southern Colorado and northern New Mexico, USA between 1988 and 2010.

2) Determine the relative importance of topography, climate, interspecific interactions, fire severity, and forest structure in influencing conifer establishment and re-sprouting densities across post-fire landscapes in southern Colorado and northern New Mexico, USA.

Completed. This objective was accomplished in two stages, represented by two separate peer-reviewed publications. First, we synthesized newly collected data describing post-fire seed production, seedling establishment, and seedling densities (see *Objective 1*). The resulting article was published in the journal *Ecological Applications* and is available online (Rodman et al. 2019). The second stage was to combine the newly collected field data with prior data throughout the region and to develop spatial data layers meant to predict future post-fire recovery. The resulting article (Chapter 4 in Rodman (2019)) is currently in review in the journal *Global Ecology and Biogeography*. Due to space limitations, only a portion of our findings from each article are presented. Thus, we turn readers to these articles for additional information. In this final report, results pertaining to *Objective 2* are presented from Rodman et al. (2019).

3) Develop a further understanding of the relationship between climate and conifer establishment following wildfire.

Completed. Similar to the descriptions in *Objective 2*, we completed this objective in two separate publications. The first publication focused on local and watershed-scale influences of climate and seed source availability on seedling densities within recent fire perimeters (Rodman et al. 2019), while the second publication used a larger dataset to model resilience to wildfire throughout the Southern Rocky Mountains Ecoregion (Chapter 4 in Rodman (2019)). In this final report, results pertaining to *Objective 3* are presented from Chapter 4 in Rodman (2019).

2. BACKGROUND

Over the past several decades, global-scale climate warming and extreme drought events have promoted increases in wildfire activity across a range of forest ecosystem types (Kasischke and Turetsky 2006, Brando et al. 2014, Singleton et al. 2019). Wildfire activity, in combination with the effects of warmer and drier conditions on tree regeneration processes, is increasing the potential for widespread forest losses (Enright et al. 2015, Stevens-Rumann et al. 2018). The rate of forest recovery following wildfire is a crucial parameter that controls the susceptibility of forests to type conversion (Tepley et al. 2018), and in dry coniferous forests of the western U.S. (i.e., lower-elevation forests with a dominant component of ponderosa pine [*Pinus ponderosa*]), early post-fire recovery differs drastically across biophysical gradients (Chambers et al. 2016,

Rother and Veblen 2016, Kemp et al. 2019). Thus, forest resilience (*sensu* Holling 1973) to wildfire is also likely to vary across complex mountainous landscapes. Spatially-explicit predictions of post-fire forest recovery (e.g., Tepley et al. 2017, Haffey et al. 2018, Shive et al. 2018) can provide insight into relative differences in forest resilience across gradients in climate and fire severity.

The empirical assessment of drivers of tree regeneration (e.g., seed production, seedling germination, site suitability) will help to identify key bottlenecks to forest persistence in a warmer, drier future (Enright et al. 2015, Davis et al. 2018b). For the successful establishment of seed-obligate conifers (i.e., those incapable of vegetative reproduction) following wildfire, viable seed must be available in sites that are suitable for germination and survival. Together, these processes define the regeneration niche (*sensu* Grubb 1977), which has a tremendous influence on the distribution of forests. Following recent wildfires throughout the western U.S., it has been noted that seedling densities of non-serotinous conifers (i.e., trees without fire-adapted canopy seedbanks) are highest near surviving trees (Haire and McGarigal 2010, Chambers et al. 2016, Kemp et al. 2016, Tepley et al. 2017) due, in part, to greater seed availability. While seed dispersal is also influenced by tree height, seed characteristics, wind speed, and animal transport, seed availability is typically highest in close proximity to mature trees (McCaughy et al. 1986). This spatial component is well-documented, yet temporal variability in seed cone production of many conifers is poorly understood because the quantification of interannual variability in seed cone production requires either long-term monitoring or reconstruction based on persistent reproductive structures (*sensu* Forcella 1981). Information regarding ponderosa pine seed cone production is available in portions of the species' range throughout the western U.S. (e.g., Burns and Honkala 1990, Krannitz and Duralia 2004, Shepperd et al. 2006, Mooney et al. 2011, Keyes and Manso 2015), but strikingly little is known about seed cone production in post-fire landscapes. This knowledge is critical for a comprehensive examination of seed availability and its influence on tree regeneration.

Overstory forest cover and post-fire vegetation also have the potential to influence conifer establishment, growth, and survival through competition, facilitation, and microclimate modification. In mixed-species systems in which conifers coexist with resprouting angiosperm species, the post-fire cover of resprouting vegetation (shrubs and trees) typically increases with fire severity (Welch et al. 2016). Competing vegetation can reduce the growth rates of some conifers (Tepley et al. 2017) and may also inhibit seedling establishment, particularly for species such as ponderosa pine that regenerate well on bare mineral soil (Pearson 1942, Schubert 1974). Overstory forest cover modifies the understory environment by altering light availability (Battaglia et al. 2002) and by moderating daily maximum temperatures and diurnal fluctuations (Davis et al. 2018a). These buffering effects have the potential to reduce the influence of climate variability on seedlings, particularly for more shade-tolerant tree species capable of establishing and surviving within densely-forested sites (Dobrowski et al. 2015). Therefore, severe wildfire can reduce the potential for conifer seedling establishment by removing seed sources, altering the competitive environment, and eliminating the microclimatic buffering effects of the canopy.

In dry forests of the western U.S., post-fire conifer seedling densities are typically greater on wetter sites such as north-facing slopes and higher elevations (Dodson and Root 2013, Rother and Veblen 2016, Tepley et al. 2017, Haffey et al. 2018, Shive et al. 2018, Kemp et al. 2019). Post-fire recovery in conifer forests is also influenced by multiyear periods of drought and by

interannual climate variability. For example, recovery is less likely in fires that are followed by abnormally dry periods (Harvey et al. 2016, Stevens-Rumann et al. 2018, Davis et al. 2019). One plausible mechanism creating these patterns is that seedling establishment for some montane conifer species is more likely in infrequent years with above-average moisture (Savage et al. 1996, League and Veblen 2006, Rother and Veblen 2017, Davis et al. 2019). Douglas-fir (*Pseudotsuga menziesii*) and ponderosa pine seedling survival is also greater under cool and moist conditions (Rother et al. 2015), with extreme drought years of particular importance to regeneration failure (Young et al. 2019).

An improved understanding of the potential limitations to post-fire conifer regeneration requires a synthetic approach that considers seed production, seedling establishment, and site suitability (Davis et al. 2018b). The goal of the projects described herein was to provide this holistic perspective. We quantified seed cone production, seedling establishment, and seedling densities at a range of spatial scales to determine the extent to which post-fire forest recovery was being limited by a range of stand attributes, biophysical factors, and regeneration processes across 15 recent wildfires in the Southern Rocky Mountains Ecoregion. Following this, we combined newly-collected field data with prior datasets to model post-fire dynamics across the region.

3. METHODS

3.1 STUDY AREA AND SITE SELECTION

Our research focused on the montane zone of the Southern Rocky Mountains Ecoregion (SRME; EPA Level III Ecoregion 21). The SRME spans 144,462 km² of complex terrain in southern Wyoming, Colorado, and northern New Mexico, USA. Forested landscapes cover 56.3% of the SRME (Homer et al. 2015) and the montane zone makes up 77.3% of the forested area (Figure 1; Rollins 2009). Dominant tree species in the montane zone include ponderosa pine, Douglas-fir, white fir (*Abies concolor* var. *concolor*), lodgepole pine (*Pinus contorta* var. *latifolia*), quaking aspen (*Populus tremuloides*), Gambel oak (*Quercus gambelii*), and blue spruce (*Picea pungens*), with relative species dominance varying with site moisture. For new field data collection (i.e., *Objective 1*), we performed surveys for post-fire recovery in 15 recent (1988-2010) wildfires that occurred in dry forests of southern Colorado and northern New Mexico, USA (Table 1, Figure 1; Fires 8-22). Sites selected for new data collection spanned a range of climatic conditions. Within fire perimeters, average January minimum temperatures range -14.9 to -6.8 C° and average July maximums range 18.1 to 30.2 C°. Total annual precipitation ranges 351 to 1049 mm, with a pronounced dry period in early summer (June and early July). Late-summer monsoons (mid-July to September) vary in importance across the study area and account for 30-45% of average annual precipitation, with increasing monsoonal contributions to the south and east (1981-2010 normals from the Parameter-Elevation Regression on Independent Slopes Model; PRISM 2018).

We selected these 15 fires as a subset of all large (> 404 ha) wildland fires in the southern portion (< 38.5 degrees N) of the Southern Rocky Mountains Ecoregion occurring from 1984-2010 (Eidenshink et al. 2007). We targeted the southern po We limited fire selection using the following criteria: 1) vegetation type – fires must have occurred in areas with dominant

components of pine-oak, ponderosa pine, or dry mixed-conifer vegetation types (Rollins 2009), 2) accessibility – fires must have occurred on accessible public land, or on large private parcels for which we were permitted access, and 3) fires must have had only minimal areas of overlap with other fire perimeters (i.e., “reburns”). Out of the 41 wildfires meeting each of these criteria, we selected and were granted permission to sample in 15. Fire severity, area burned, pre-fire vegetation, and average climate varied across the fires studied (Rodman et al. 2019).

Table 1: A summary of post-fire sampling of conifer establishment and abundance throughout the 22 surveyed wildfires in the Southern Rocky Mountains Ecoregion. New data collection (i.e., Objective 1) took place in fires 8-22.

Map ID	Fire Name	Area (ha)	Fire Year	N. Destructive Samples		Field Plots
				Ponderosa Pine	Douglas-Fir	
1	Hensel	5843	2002	0	0	39
2	Bobcat	3695	2000	0	0	117
3	Overland	1308	2003	86	5	94
4	Eldorado	405	2000	75	8	50
5	High Meadows	3888	2000	62	12	89
6	Buffalo Creek	3963	1996	81	5	120
7	Hayman	52373	2002	68	11	205
8	Mason	4461	2005	16	2	37
9	Mato Vega	5312	2006	0	0	36
10	Missionary Ridge	27891	2002	12	5	33
11	Spring	9730	2002	26	0	45
12	H12	1778	2010	32	0	40
13	York	1314	2001	16	0	40
14	Saw	1259	1988	7	10	38
15	West Fork	2200	2008	0	0	40
16	Ponil Complex	36051	2002	19	1	39
17	Hondo	3339	1996	0	0	31
18	Montoya	1666	2002	0	0	45
19	Pine Canyon	1656	2005	43	0	39
20	Borrego	5211	2002	44	1	45
21	Lakes	1742	2002	18	13	48
22	Viveash	9093	2000	18	19	31
Total		184177	1988-2010	623	92	1301

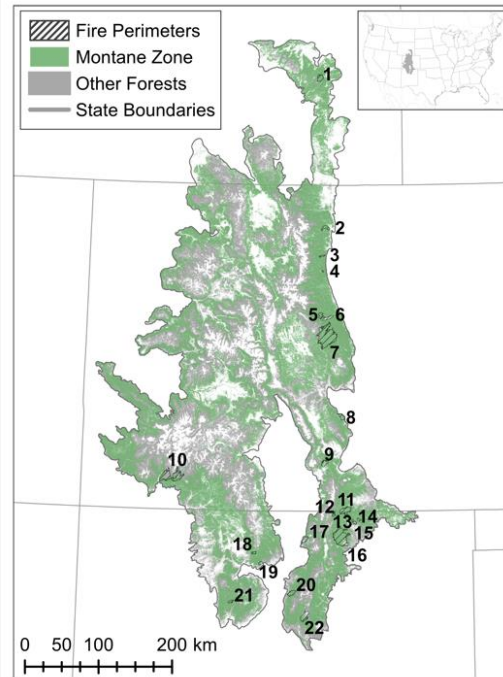


Figure 1: The locations of 22 recent (1988-2010) wildfires in the Southern Rocky Mountains Ecoregion that were sampled for post-fire conifer establishment and abundance. Map numbers correspond to “Map ID” in Table 1.

We used a nested plot design with 8-12 transects within each fire perimeter and 3-6 plots along each transect. To identify the start of each transect, we first identified contiguous areas of low-, moderate-, and high-severity fire using thematic maps of dNBR (differenced Normalized Burn Ratio)-derived fire severity from the Monitoring Trends in Burn Severity project (Eidenshink et al. 2007). To locate each transect within a relatively homogenous area, we selected potential sites as contiguous patches of each severity class that exceeded 300 m in diameter. We excluded any areas with reforestation activities from site selection. Next, we created an accessibility layer in which we identified areas within each fire that were between 100 and 500 m of a system road or major trail. Finally, we identified 3-4 patches of each fire severity class that intersected the accessibility layer and spanned the geographic extent of the fire. We randomly located transect starts within each selected patch. Along each transect, we established plots with a 60-m systematic spacing and random offsets (10 m at a random azimuth). We allowed the number of transects and plots to vary within each fire perimeter based on the number of suitable patches identified, with the goal of establishing a total of 40 plots per fire (total n = 555).

3.2 FIELD DATA COLLECTION

Following Harvey et al. (2016), we used a variable-sized plot design to survey post-fire densities of conifer seedlings and resprouting angiosperms. Plot sizes were species-specific and based on initial surveys of abundance in each plot. For tree species with fewer than 25 post-fire stems within the full 15-m radius circular plot (707 m²), we surveyed all stems. If more than 25 stems of a species were present in the full plot, sampling areas were reduced to the following: 25-100 stems - 120 m², 101-500 stems - 30 m², > 500 stems - 10 m². We defined seedlings as all conifers establishing following fire (as determined from bud scars [*sensu* Urza and Sibold 2013] and ring counts from increment cores), but we did not survey first-year germinants because of the high mortality rates for these individuals. Because seedling ages derived from bud scars can underestimate true seedling ages (Hankin et al. 2018), we may have slightly overestimated post-fire seedling densities in some low- and moderate-severity plots. However, these biases are greater for older and larger seedlings, for which we also used increment cores to verify ages.

To develop field-derived estimates of fire severity and to quantify pre- and post-fire forest structure, we recorded the species and diameter at breast height (DBH; 1.37 m above ground level) of all live and dead overstory trees within each plot that likely pre-dated each fire. We determined pre-fire status of trees using stem diameter (> 10 cm DBH for conifers and > 5 cm for angiosperms; Table 2), level of decay, and char characteristics. We used branch morphology, wood characteristics, and the color and texture of remaining bark to identify the species of each dead individual. At the plot-level, we calculated the total pre-fire basal area of all tree species as a potential indicator of site productivity. We calculated field-derived fire severity as the percentage of total pre-fire basal area killed during the fire. At each plot center, we recorded the distance to the closest surviving mature conifer using a laser rangefinder. If these distances exceeded 500 m (the distance limitation of the instrument) or if no trees were visible from plot center, we measured the distance from plot center to the closest mature conifer using 2014 or 2015 aerial imagery (USFS 2015). Lastly, we quantified ground cover on each plot using four 1-m² quadrats and noted any evidence of grazing or browse damage by cattle or other ungulates.

To quantify ponderosa pine seed cone production following wildfire, we used the cone abscission scar method (Redmond et al. 2016). We performed these surveys in 8 of the 15 surveyed fires, a subset meant to span the geographic and climatic range of our sites. For brevity, we do not present the results of these surveys here, but they are discussed in detail in Rodman et al. (2019). In addition, we destructively sampled 696 ponderosa pine, Douglas-fir, lodgepole pine (*Pinus contorta*), Gambel oak (*Quercus gambelii*), and quaking aspen (*Populus tremuloides*) seedlings and stems to characterize important years for tree seedling establishment. We determined the establishment year of each conifer seedling following the methods of Rother and Veblen (2017). Briefly, this involves taking cross-sections of a stem above- and below-ground, and dating the innermost ring on the sample closest to the root-shoot boundary (Telewski 1993). For resprouting angiosperm trees, we used the innermost ring from a single sample near ground level. We limit the discussion of these results to the 302 ponderosa pine and Douglas-fir samples and companion data collected in the Colorado Front Range in a previous study (Rother and Veblen 2017) (Table 1; Fires 8-22). The remaining species (i.e., lodgepole pine, Gambel oak, and quaking aspen) are also presented in Rodman et al. (2019).

For the synthesis of post-fire regeneration across the SRME, we paired these newly collected data (of seedling densities and the timing of seedling establishment) with datasets in five prior or ongoing studies (Ouzts et al. 2015, Chambers et al. 2016, *In Prep*, Rother and Veblen 2016, 2017). Though methods varied slightly among studies, field data included either surveys of post-fire seedling density (Ouzts et al. 2015, Chambers et al. 2016, Rother and Veblen 2016) or quantification of the timing of seedling establishment (Rother and Veblen 2017) in ways that are compatible with the methods used in our new field data collection. The total sample size of post-fire regeneration plots and destructive samples in the combined dataset is given in Figure 1 and Table 1. Because the manuscript developed from these data is currently under review and results may change, only a subset of the results of analyses are presented.

3.3 SPATIAL DATASETS

Within each surveyed wildfire, we extracted elevational data (USGS 1999) at c. 30 m resolution, and climate data from the PRISM (PRISM 2018) and gridMET datasets (Abatzoglou 2013). We used the elevational data to calculate terrain variables of topographic position index (TPI; Weiss 2001) and heat load index (HLI; McCune and Keon 2002). TPI is the elevational difference between a given location and its surroundings, where low values are indicative of valley bottoms and high values are indicative of ridgetops. HLI combines slope angle, latitude, and transformed aspect to estimate solar heating in a given site. We used gridded climate data to calculate climatic water deficit (CWD) and actual evapotranspiration (AET) within each fire perimeter using equations in Lutz et al. (2010). However, for analyses in Chapter 4 of Rodman (2019) we used the equations of Dobrowski et al. (2013). While CWD provides an estimate of the intensity of drought stress because it estimates unmet atmospheric moisture demand, AET is an indicator of site productivity because high values are indicative of sites with high availability of both moisture and energy (Stephenson 1998). We also extracted total precipitation during the growing season (April-September), which is related to post-fire seedling establishment (Rother and Veblen 2017). Lastly, we characterized the survival of mature conifers, and thus seed availability, throughout each fire using semi-supervised classification of 1-m aerial imagery from the National Agriculture Imagery Program (NAIP; USFS 2015). Image classification of mature conifers exceeded 90% accuracy (Rodman et al. 2019).

3.4 ANALYTICAL METHODS

Objective 2 – From Rodman et al. (2019)

To quantify the influence of seed source availability, climate, and terrain on post-fire seedling densities of ponderosa pine and Douglas-fir, we used generalized linear mixed models (GLMMs; *sensu* Bolker et al. 2009) in the “glmmTMB” package (Brooks et al. 2017) in R (R Core Team 2018). Potential predictors in each GLMM included factors related to 30-year average climate, 3-year post-fire climate, fire severity, topography/terrain, herbivory, densities of other tree species, pre-fire forest structure, and post-fire groundcover. Because of the hierarchical structure of data collection, we used nested random intercepts (transect within fire) to account for spatial dependence of plot data within each transect and across each fire. Semivariograms of model residuals indicated very little spatial dependence with this random effect structure (nugget:sill ratio near 1; Bivand et al. 2013). To account for differences in sampling area among plots (due to the variable-sized subplots used in this study), we also included an offset term of

“log(subplot area)” for each species on each plot (Zuur et al. 2009). Following the development of initial zero-inflated GLMMs with a Poisson error structure, we used simulation-based tests of model residuals in the “DHARMA” package (Hartig 2018) in R to examine issues of dispersion. Our initial models were underdispersed and we therefore used a generalized Poisson error structure – a preferred distribution in these cases (Hilbe 2014). We used an information theoretic approach to select variables for inclusion in final statistical models (Burnham and Anderson 2002). To make spatially-explicit predictions of post-fire seedling densities at a 30-m resolution throughout each fire perimeter, we also developed a second set of statistical models for each species that included only predictors that could be quantified throughout the entirety of each fire (i.e., climate, mature seed tree presence from image classification, terrain). Lastly, we summarized the adequacy of regeneration throughout each fire by comparing predicted seedling densities to some of the lowest reported tree densities in ponderosa pine and dry mixed-conifer forests in the Southwest (Reynolds et al. 2013, Rodman et al. 2017). Specifically, we quantified the percentage of area within each fire perimeter and of total fire area that were below 25 ponderosa pine seedlings ha⁻¹ and 10 Douglas-fir seedlings ha⁻¹, across the total burn area and within high-severity areas (i.e., total canopy mortality), to assess resilience.

Objective 3 – From Chapter 4 of Rodman (2019)

To quantify the importance of interannual climate variability to post-fire establishment of ponderosa pine and Douglas-fir, we modeled annual establishment suitability using boosted regression trees (BRTs). For the response variable in BRTs, we aggregated counts of establishing seedlings (by year and by species) to the level of individual fires to accommodate variation in plot design between Rother and Veblen (2017) and Rodman et al. (2019). We then scaled and centered (i.e., z-score transformation) annual seedling counts using the series-wide mean and standard deviation in each fire, such that positive values in a given year had above-average post-fire establishment in a given fire. This transformation ensures that the response variable is on a similar scale across fires and accounts for differences in sample depth. As potential predictors of annual seedling establishment, we extracted CWD, AET, and precipitation during the April-September growing season in each year (1981-2015) within each fire perimeter. Next, we z-score transformed values of each climate variable within each fire based on the baseline period of 1981-2015. We also created a variable of “time since fire”, representing the number of years between fire occurrence and seedling establishment. Because sample sizes for Douglas-fir were relatively low, and because preliminary analyses indicated that the two species showed relatively similar climate-establishment relationships, we developed a single BRT model for both species combined. We used the “gbm.step” function in the “dismo” package (Hijmans et al. 2017) in R (R-Core-Team 2018) to select the optimal number of trees in each BRT model. We used a Gaussian loss function, a learning rate of 0.001, a step size of 5, and a complexity of 2, allowing for two-way variable interactions (Elith et al. 2008). The final BRT model included 2540 trees. We assessed the accuracy of fitted BRTs by comparing observed and predicted establishment suitability (i.e., z-scores of seedling counts), both in the entire dataset and in spatially-stratified cross-validation (withholding data from one fire in each of the 16 folds as a test set).

4. RESULTS

Objective 2 – From Rodman et al. (2019)

Final GLMMs of post-fire ponderosa pine seedling density – created using all field-derived and spatially-extensive variables as potential predictors – included 30-year average AET, 30-year average CWD, field-derived distances to mature conifers, pre-fire basal area, percent basal area mortality, and post-fire vegetation characteristics (Figure 2a). Low 30-year average CWD and high 30-year average AET, together indicative of productive areas with abundant moisture, were associated with higher seedling densities (Figure 2a). Interestingly, 30-year averages of CWD and AET were better predictors of ponderosa pine seedling density than were 3-year post-fire AET and CWD. Including 3-year post-fire climate variables did not improve predictive accuracy. Plots that were adjacent to surviving mature conifers, had higher pre-fire basal area, and burned at higher severity (i.e., greater percent basal area mortality) had higher densities of ponderosa pine (Figure 2a). Grass cover and Gambel oak sprouting densities were negatively related to ponderosa pine density, while post-fire Douglas-fir seedling density was positively related to ponderosa pine density (Figure 2a). The Douglas-fir model with both field-derived and spatially-extensive variables did not improve upon the model including only spatially-extensive variables, thus we only present the latter model for Douglas-fir.

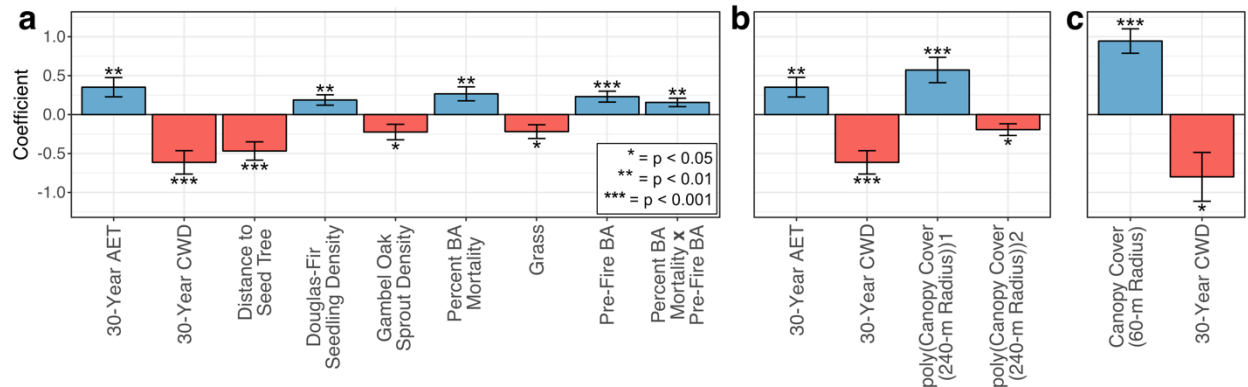


Figure 2: Standardized coefficients and significance levels for each of the predictors included in generalized linear mixed models predicting postfire (a, b) ponderosa pine and (c) Douglas-fir seedling densities. Error bars are \pm one standard error of the coefficient estimate. Models were developed from (a) all potential predictors (both field-derived and the spatially-extensive variables) and (b, c) spatially-extensive predictors only (for later use in spatial modeling). We do not present a model for Douglas-fir seedling density using field-based predictors because these did not improve model fit. Coefficients are for the conditional models only and zero-inflation terms or random intercept coefficients are not shown. Non-linear predictors are preceded by “poly” and variable interactions are given by linking two variable names with “x”.

GLMMs developed for spatially-explicit models of ponderosa pine and Douglas-fir seedling densities were relatively similar to one another, including both 30-year average CWD and post-fire canopy cover of mature conifers as top predictors, but also had some important differences (Figure 2b, 2c). The ponderosa pine model included 30-year average CWD, 30-year average AET, and post-fire canopy cover of mature conifers, with 30-year CWD being the most important predictor. Low 30-year average CWD and high 30-year average AET were associated with higher ponderosa pine densities (Figure 2b). The Douglas-fir model included only 30-year average CWD and post-fire canopy cover of mature conifers. Canopy cover was more important than was 30-year average CWD for Douglas-fir (Figure 2c). The most notable difference between the two species was the relationship with post-fire canopy cover of mature conifers,

which we assessed at a range of neighborhood sizes (30-600 m radii in 30-m increments). Ponderosa pine densities were highest in areas with intermediate (46%) canopy cover and the most influential neighborhood size was relatively broad: a 240-m radius (Figure 2b). A non-linear term for canopy cover led to a slightly improved model fit ($\Delta AIC = 1.8$) and a more ecologically realistic response given the shade-intolerant nature of ponderosa pine. In contrast, Douglas-fir densities were highest in dense stands (100% cover) and a localized 60-m neighborhood size was most influential (Figure 2c), consistent with overstory microclimatic buffering and the greater shade tolerance of this species.

Spatially-explicit predictions of post-fire seedling densities for each species indicated that 42% and 69% of total fire area had densities below 25 ponderosa pine and 10 Douglas-fir seedlings ha^{-1} , respectively (Figure 3, Figure 4). In the portions of these fires with total canopy mortality (high-severity), predicted densities were lower. We estimated that 57% of the total high-severity area did not exceed 25 ponderosa pine seedlings ha^{-1} and 79% of the total high-severity area did not exceed 10 Douglas-fir seedlings ha^{-1} . Recovery also varied substantially among fires. For example, the Montoya Fire had 0% of total fire area exceeding 25 ponderosa pine and 10 Douglas-fir seedlings ha^{-1} , while the Saw Fire had 100% (ponderosa pine) and 98% (Douglas-fir) of fire area above these same density thresholds (Figure 3, Figure 4). At the fire-level, the percentage area exceeding density thresholds was positively correlated with pre-fire dominance of each species ($\rho = 0.55$ for ponderosa pine, $\rho = 0.38$ for Douglas-fir) and negatively correlated with the percentage of fire area with total canopy mortality ($\rho = -0.50$ for ponderosa pine, $\rho = -0.52$ for Douglas-fir). There were weaker relationships with mean 30-year CWD within fire perimeters ($\rho = -0.15$ for ponderosa pine, $\rho = -0.25$ for Douglas-fir), indicating that CWD is operating at a finer spatial scale.

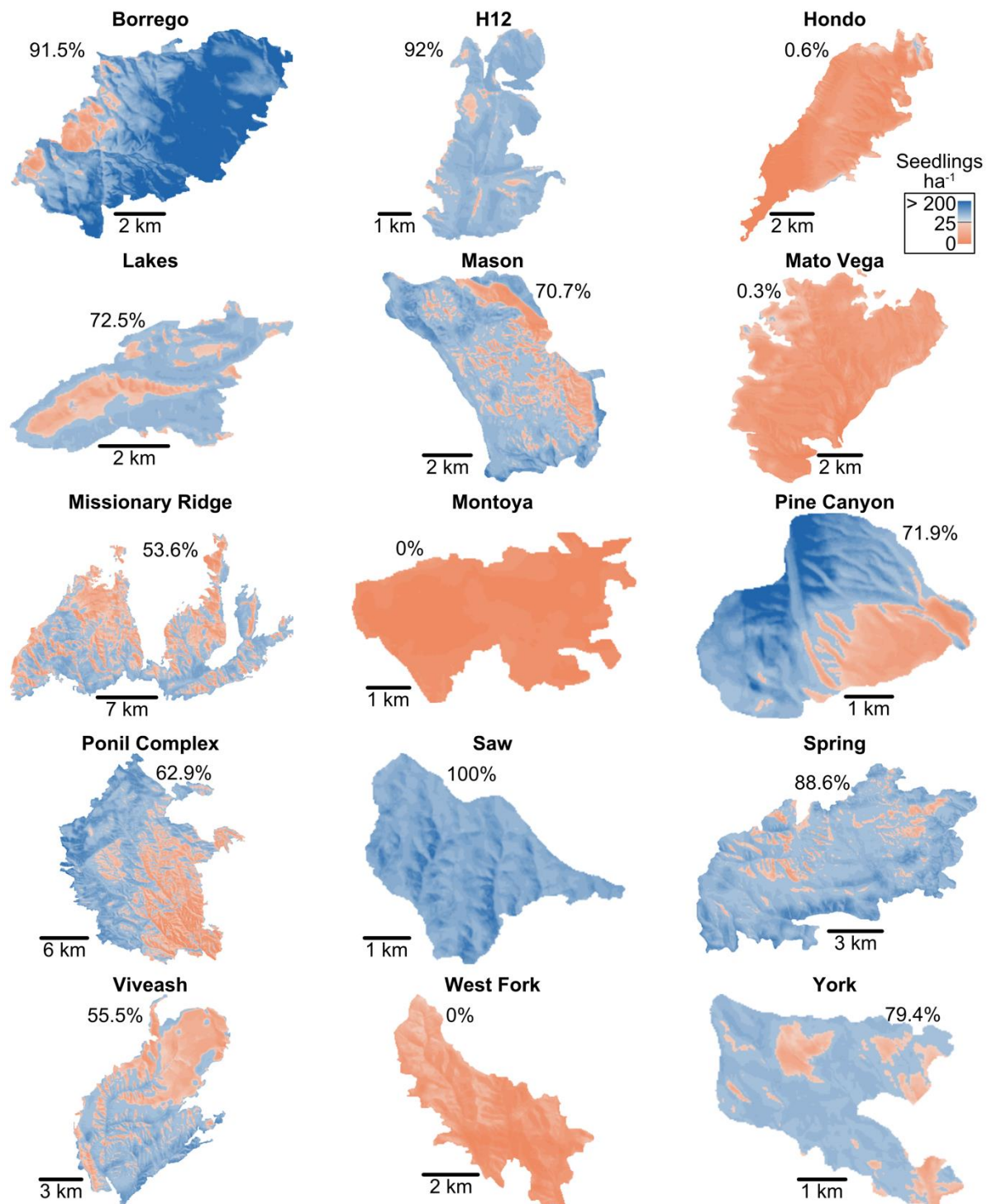


Figure 3: Predicted ponderosa pine seedling densities throughout each surveyed fire in southern Colorado and northern New Mexico based on GLMMs using only spatially-extensive predictors. The percentage values in each panel give the percentage of fire area exceeding a density threshold of 25 seedlings ha^{-1} , which corresponds to some of the lowest historically reported densities for this species in ponderosa-pine dominated forests of the Southern Rocky Mountains and Southwest (Rodman et al. 2017). Blue areas in each map exceed this threshold while red areas are below this threshold. Note that cartographic scales differ among panels.

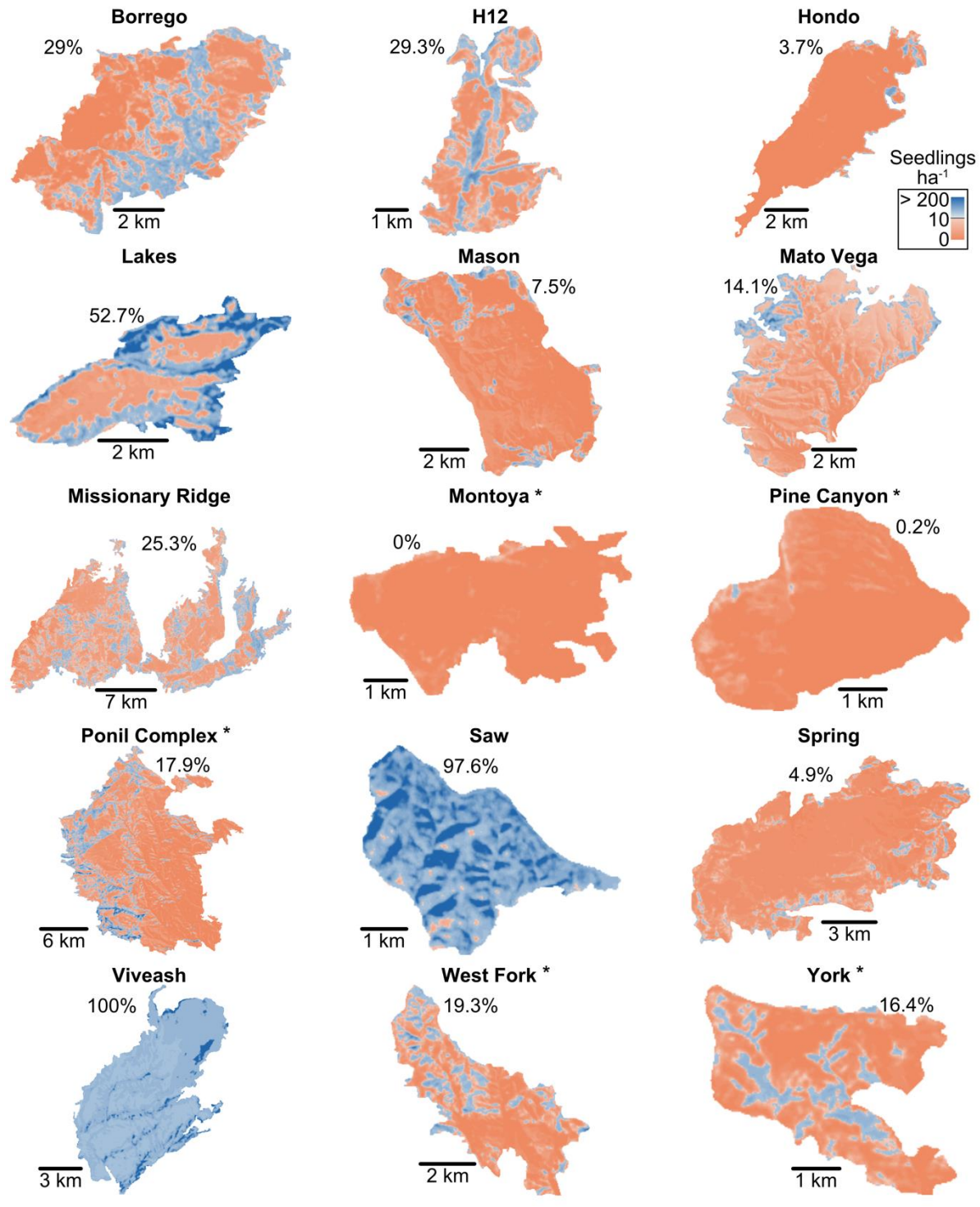


Figure 4: Predicted Douglas-fir seedling densities throughout each surveyed fire in southern Colorado and northern New Mexico based on GLMMs using only spatially-extensive predictors. The percentage values in each panel give the percentage of fire area exceeding a density threshold of 10 seedlings ha^{-1} , which corresponds to some of the lowest historically reported densities for this species in dry mixed-conifer forests of the Southern Rocky Mountains and Southwest (Rodman et al. 2017). Blue areas in each map exceed this threshold while red areas are below this threshold. Fire names followed by (*) are those in which Douglas-fir represented less than 10% of pre-fire basal area. These fires were excluded from summaries of spatial models. Note that cartographic scales differ among panels.

Objective 3 – From Chapter 4 of Rodman (2019)

Final BRT models of seedling establishment included time since fire, as well as growing season precipitation and annual AET during the establishment year (Figure 5). Annual CWD did not increase predictive accuracy. The most influential predictor in BRTs was time since fire (relative influence = 43.2%), but growing season precipitation (31.3%) and annual AET (25.4%) still showed strong relationships with seedling establishment. Seedling establishment was most likely from 1-10 years after fire occurrence, with a peak at 4-6 years following fire (Figure 5a). Establishment was most likely during wet years (above-average growing season precipitation and annual AET; Figure 5b, 5c). Correlations between observed and predicted establishment suitability were 0.59 in the full dataset and 0.42 in spatially stratified cross-validation, indicating the utility of these climate-establishment models when predicting to new areas.

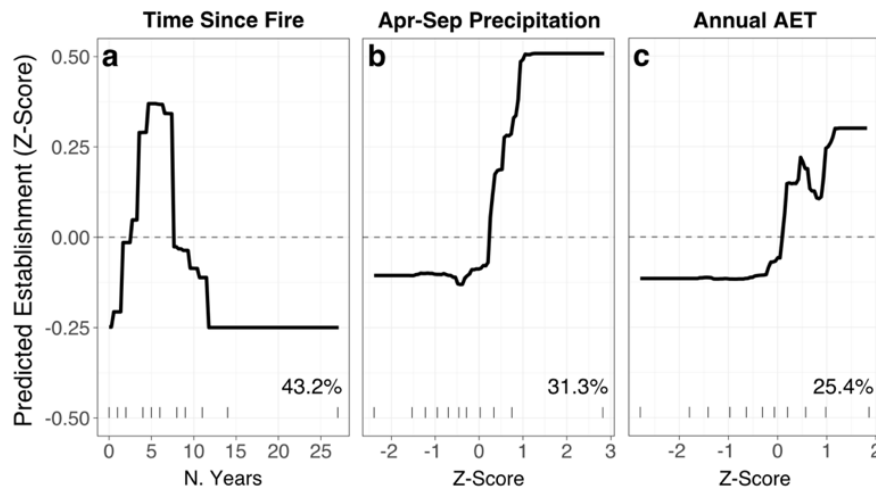


Figure 5: The influence of time since fire (a) and interannual climate variability (b, c) on post-fire establishment for ponderosa pine and Douglas-fir. Subfigures show the marginal influence of each predictor (y-axis) across the range of values observed in the data (x-axis). X-axis values at which a solid line is above zero (i.e., dashed lines) indicate a positive relationship between that variable and counts of establishing seedlings. Percentages in each subpanel give relative influence.

5. DISCUSSION

Limited recovery of seed-obligate conifers has been widely documented following recent wildfires throughout the western U.S. (e.g., Harvey et al. 2016, Rother and Veblen 2016, Shive et al. 2018, Stevens-Rumann et al. 2018, Kemp et al. 2019), yet the spatial and temporal variability in factors limiting post-fire forest recovery are still poorly understood. Building on the existing knowledge of recovery processes in dry forests, we found that variability in post-fire conifer seedling density related to gradients in climate and fire severity, and seedling densities were highest on mesic sites and near surviving conifers. Douglas-fir and ponderosa pine post-fire seedling densities were relatively low across a substantial percentage of the total burned area in 15 recent wildfires. Interannual climate also influenced tree establishment. Douglas-fir and ponderosa pine seedlings had greater establishment abundance within 10 years of fire occurrence and in years with abundant moisture (growing season precipitation and AET). Together, the initial filter of seed availability (a combination of seed production and proximity to mature conifers) and the secondary filter of climate limited conifer forest recovery across dry forests in the Southern Rocky Mountains Ecoregion.

5.1 SPATIAL LIMITATIONS TO SEED AVAILABILITY AND OTHER EFFECTS OF LIVE TREES

Fire severity, measured here using a combination of variables including field-derived distance to mature conifers, percent basal area mortality, post-fire canopy cover of mature conifers in aerial imagery, and satellite-derived RdNBR, was one of the factors best predicting post-fire ponderosa pine and Douglas-fir seedling densities. Fire severity relates to the availability of live conifers throughout the landscape, which then drives spatial patterns of seed-availability. Surviving trees also modify temperature (Davis et al. 2018a), relative humidity (Paritsis et al. 2015), and light availability in the understory (Battaglia et al. 2002), thereby influencing seedling survival and resource availability in harsh post-fire environments. While canopy moderation may benefit both ponderosa pine and Douglas-fir, Douglas-fir is better adapted to benefit from microclimatic buffering (*sensu* Dobrowski et al. 2015) given its greater ability to tolerate the shaded understories of densely forested areas (Burns and Honkala 1990). For example, the areas predicted to have the highest densities of ponderosa pine seedlings were under intermediate levels of canopy cover (i.e., 46% in a 240-m radius). In contrast, Douglas-fir had higher seedling densities in dense stands (i.e., 100% cover in a 60-m radius). At a fine scale, we found that plots with high fire severity (as indicated by high percent basal area mortality), but in close-proximity to seed trees had high post-fire ponderosa pine seedling densities, likely due to fire-induced modifications of the seedbed and increased light availability on these sites (thus benefitting shade-intolerant ponderosa pine). Localized patches of high-severity fire may drive the abundant, aggregated establishment of ponderosa pine due to the presence of an adjacent seed source as well as bare mineral soil, available light, and increases in growing space (Sánchez Meador et al. 2009, Larson and Churchill 2012). Fire severity, influencing seed availability and conditions in the understory environment, is one of the most important factors limiting the recovery of seed-obligate conifers in post-fire environments.

5.2 CLIMATE AND SITE SUITABILITY AS CONSTRAINTS ON POST-FIRE REGENERATION

Average climate (described by 30-year CWD and AET) was another strong predictor of post-fire densities for both ponderosa pine and Douglas-fir. Consistent with the findings of other studies (e.g., Dodson and Root 2013, Chambers et al. 2016, Kemp et al. 2016, Rother and Veblen 2016), we found that moisture-limited sites at low elevations and on southerly aspects typically had low conifer seedling densities, even in areas adjacent to a seed source. Many previous studies have utilized individual climate variables such as precipitation and temperature or terrain variables such as aspect and elevation to explain variability in post-fire conifer density. Water balance metrics such as CWD and AET provide a more useful alternative because they effectively combine the influence of climate, topography, and soils, and are functionally tied to the environmental conditions experienced by plants (Stephenson 1998, Dilts et al. 2015). When calculated at fine spatial resolutions that mirror the operational scales of post-fire recovery processes (as done in this study), AET and CWD are useful and complementary predictors of post-fire recovery in semi-arid landscapes and are helpful indicators of susceptibility to fire-driven conversions in vegetation.

At an annual resolution, extreme drought years influence longer-term forest trajectories, likely by increasing seedling mortality (Young et al. 2019), while wetter years lead to pulses of conifer establishment (Rother and Veblen 2017, Davis et al. 2019). It is now increasingly acknowledged that interannual plays a key role in conifer establishment throughout the U.S. West (Savage et al. 1996, League and Veblen 2006, Rother and Veblen 2017, Andrus et al. 2018, Davis et al. 2019). However, the extent to which post-fire climate influences seed production and seedling mortality remain key questions for future research. These empirical studies are needed to better inform demographic models that tie interannual climate variability to specific components of the conifer reproductive cycle (e.g., Feddema et al. 2013, Savage et al. 2013, Petrie et al. 2017, Davis et al. 2019).

Additional factors that helped to predict post-fire seedling densities included seedbed characteristics, post-fire recovery of other tree species, and pre-fire forest density. For example, our results indicated that grass cover and Gambel oak density both had negative relationships with ponderosa pine density at the stand-scale. Bunch grasses (e.g., *Festuca arizonica*) may compete with ponderosa seedlings for soil moisture (Pearson 1942), potentially limiting seedling densities (Flathers et al. 2016). In contrast to our findings, previous studies have noted that ponderosa pine may have weak (Owen et al. 2017) or even strong (Ziegler et al. 2017) positive spatial associations with resprouting angiosperm trees in post-fire environments. Gambel oak is believed to facilitate the establishment of another southwestern pine species (i.e., *Pinus edulis*; Floyd 1982) through microclimatic buffering and perhaps by attracting avian dispersers (such as corvids). Therefore, our finding of a negative relationship between Gambel oak density and ponderosa pine density may also reflect the occupancy of different site types rather than competitive or inhibitory interactions between these species. We also noted that high pre-fire basal area and post-fire Douglas-fir seedling density were positively related to ponderosa seedling density, perhaps indicative of wetter sites with better growing conditions. Post-fire seedling density is locally variable, reflecting variability in the seedbed, local vegetation characteristics, and growing conditions (as influenced by moisture availability and topoclimate).

5.3 LANDSCAPE-SCALE VARIABILITY IN RESILIENCE TO FIRE

Spatial variability in conifer seedling density was effectively predicted throughout each fire using statistical models developed from field data and spatially-extensive datasets. Using these predictions, we determined that ponderosa pine and Douglas-fir regeneration was below the lowest reported historical tree densities in large percentages (42% and 69%, respectively) of the total area burned throughout 15 recent wildfires in southern Colorado and northern New Mexico, USA. Importantly, there was also pronounced variability in forest recovery among fires. Individual fire events ranged widely in post-fire recovery (with both species ranging from 0-100% across fires), which makes broad generalizations about causal mechanisms difficult. Still, much of this limited regeneration could be attributed to a lack of post-fire canopy cover of mature conifers and the unfavorable climate in portions of the surveyed sites (specifically 30-year average AET and CWD). In addition, recovery among fires was strongly related to differences in pre-fire species dominance, indicative of important legacy effects. Our spatial models provided an effective means of scaling stand-level observations to extensive post-fire landscapes (Tepley et al. 2017, Haffey et al. 2018, Shive et al. 2018), thus permitting broader inferences about vulnerability to post-fire vegetation type conversion.

Projections of future shifts from forest to non-forest vegetation types are inherently uncertain due to unknown future climatic variability as well as uncertainties about rates and specific drivers of vegetation change. Because our surveys were performed in relatively recent wildfires (1988-2010), it may be too early to suggest that transitions to non-forest vegetation types are permanent (Baker 2018). Still, the spatial variability in predicted densities across our study area indicates that some site types (e.g., xeric sites and those in the interior of high-severity patches) are more vulnerable to vegetation type conversions than others. Forest response to wildfire is often presented as a simplistic binary outcome of resilient versus non-resilient based on observations over periods of one to a few decades, yet a more nuanced approach to forest resilience considers rates of recovery, which can then create gradients of “relative resilience” across the landscape (Tepley et al. 2017, 2018, Shive et al. 2018). Given the importance of canopy cover and 30-year average CWD in predicting densities of both ponderosa pine and Douglas-fir, results from the current study imply that under continued warming and altered fire activity, some forested areas in the Southern Rocky Mountains are likely to undergo fire-driven conversions to non-forested vegetation (Parks et al. 2019). Similarly, because growing season precipitation and annual AET appear to be important drivers of interannual variability in post-fire seedling establishment

6. CONCLUSION

As a result of funding from Joint Fire Science Program (GRIN award number 17-2-01-4), we were able to expand field surveys and lab projects involved in Kyle Rodman’s dissertation work (Rodman 2019). We substantially exceeded our initial estimates of new field data collection involved in the project and have developed a combined dataset that spans much of the Southern Rocky Mountains Ecoregion. As deliverables, we have presented this research at several workshops and professional conferences, co-organized a webinar with the Southern Rockies Fire Science Network and Utah State University, produced one peer-reviewed publication, and have two additional publications under review or in preparation (Appendix B). Furthermore, we developed new insight in several key areas that can be directly applied to on the ground management action. Specifically, we note four key findings that align with findings from other dry forests throughout the U.S. West.

6.1 KEY FINDINGS

1) Post-fire seedling densities were highest near surviving trees

While Douglas-fir and ponderosa pine seedlings were occasionally found 300 m or more from mature trees, the vast majority of seedling establishment occurred near surviving seed sources. The spatial variability in tree survivorship is therefore a crucial indicator of the ability of dry forests to re-establish following high-severity fire, and the locations of surviving trees can be quantified using remotely-sensed data at varying resolutions (NAIP at 1-m; LANDSAT-derived RdNBR at 30 m).

2) Post-fire seedling densities were also higher on wetter sites (i.e., higher elevations and northerly aspects)

Site moisture clearly plays an important role in post-fire vegetation trajectories, both by influencing the species present prior to the fire (and therefore the propagules available for post-fire establishment) and the suitability of different portions of the landscape for tree seedlings. Proxies for site moisture such as elevation and aspect are useful to generalize about different portions of a burned landscape that may be more or less suitable for seedling establishment, but water balance metrics such as AET and CWD may be more useful alternatives because they integrate the effects of climate, available water holding capacity in the soils, and aspect-driven differences in solar radiation.

3) Local vegetation and forest structure matter to regeneration

Post-fire ponderosa pine seedling densities were higher in areas with greater pre-fire stand basal area and more post-fire Douglas-fir seedlings, indicative of the importance of local site productivity and moisture. Factors that could not be fully explained using water balance metrics. Thus, finer-resolution soils data and additional terrain variables (e.g., topographic wetness index) may help to explain localized variation in site productivity. Ponderosa pine seedling densities were lower in areas with high grass and oak cover. Previous research indicates that dense grasses inhibit ponderosa pine seedling establishment. However, the relationship with oak density is still an open question. Douglas-fir seedling densities were highest in areas with dense surviving tree cover, while ponderosa pine densities were highest under moderate forest densities and in localized patches of high-severity fire.

4) Seedling establishment of both ponderosa pine and Douglas-fir related to interannual climate variability and time since fire.

New Douglas-fir and ponderosa pine seedling establishment were greatest between 1-10 years following fire. Previous studies note that there can be an initial pulse of establishment following fire occurrence in dry forests. However, new tree establishment may continue to occur for many years after a fire. Additional research is needed in older fires to determine the extent to which initial post-fire trajectories are truly indicative of longer-term trends. We also found that wet years were beneficial to new seedling establishment. Years with above-average precipitation in the growing season, and years with high AET generally had more abundant seedling establishment. While temperature is expected to increase across much of the southern Rocky Mountains over the next century, precipitation trends are highly uncertain.

6.2 IMPLICATIONS TO MANAGEMENT

Continued climate warming will increase the vulnerability of many low-elevation forests to conversion to non-forest vegetation types, and this presents complex challenges to land managers. In particular, weather is expected to become more conducive to fire occurrence and spread, and a warming climate will also alter post-fire forest recovery (Enright et al. 2015). Adequately addressing these challenges requires consideration of societal values and forest ecosystem services, as well as the best possible technical understanding of the potential for success of a variety of possible management interventions (Higuera et al. 2019). Potential management options include actions that attempt to forestall change through enhanced ecosystem resistance to fire effects, interventions aimed at improving post-fire resilience, and

actions such as assisted migration aimed at facilitating ecosystem transformation to systems consistent with a changing climate (Millar et al. 2007, Halofsky et al. 2014). All management interventions have considerable risk due to uncertainties in predicting the rate and pattern of future climate change and the complexity of climate impacts on ecosystem dynamics. Therefore, a diverse range of approaches to adaptation and management should be considered (Millar et al. 2007, Baker 2018).

Currently, reforestation is one of the most common management responses to large severe fires in the western U.S. (North et al. 2019), and the effectiveness of post-fire planting can vary widely (e.g., 0-96% survival in planted sites throughout Arizona, California, and New Mexico; Ritchie and Knapp 2014, Ouzts et al. 2015). The likelihood of successful reforestation can benefit from the type of site-specific research on regeneration processes presented in the current study. If reforestation of recently-burned areas remains an important goal, relatively cool/wet sites should be prioritized first because seedling survival in these areas is likely to be greatest, now and into the future. Within these wetter areas, planting units should be limited to locations where available seed sources are most distant (Stevens-Rumann and Morgan 2019). The statistical analyses and spatial models presented here help to locate these types of sites in heterogenous burned landscapes by identifying areas that are climatically suitable, but in which recovery is limited by the proximity to live conifers. In addition, prioritizing plantings in wetter years would be likely to benefit treatment success, though planning for artificial regeneration treatments is a relatively inflexible multi-year process. Our results are also important in informing discussions among stakeholders of the likelihood of future changes in the extent of forest cover, the probable changes in forest ecosystem services, and the costs and benefits of a range of adaptation strategies.

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APPENDIX A: CONTACT INFORMATION FOR KEY PROJECT PERSONNEL

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APPENDIX B: LIST OF COMPLETED/PLANNED PRODUCTS

Completed

Conference and Workshop Presentations

- Rodman, K. C., Battaglia, M. A., Chambers, M. E., Fornwalt, P. J., Holden, Z. A., Kolb, T. E., Rother, M. T., Ouzts, J. R. & T. T. Veblen. 2019. Recent and projected future trends in post-fire regeneration for two conifer species in the southern Rocky Mountains. *North American Forest Ecology Workshop*. Flagstaff, AZ.
- Rodman, K. C., Veblen, T. T., Chapman, T. B., Rother, M. T., Wion, A. P., & M. D. Redmond. 2019. Limitations to recovery following wildfire in dry forests of southern Colorado and northern New Mexico, USA. *International Association of Landscape Ecology*. Fort Collins, CO.
- Rodman, K. C., & T. T. Veblen. 2018. Friends or Foes? Interspecific interactions in post-fire environments. *Southern Rockies Fire Science Network: Gambel Oak Management Symposium*.
- Rodman, K. C., Veblen, T. T., Chambers, M., Rother, M., & J. R. Ouzts. 2017. Modeling the influence of climate and local site factors on post-fire regeneration in the Southern Rocky Mountains Ecoregion. *Natural Areas Conference*. Fort Collins, CO.

Dissertations/Theses

- Rodman, K. C. 2019. Forest cover change and post-fire response in the southern Rocky Mountains. University of Colorado Boulder. Available online at: < <https://search-proquest-com.colorado.idm.oclc.org/docview/2299449454>>

Peer-Reviewed Publications

- Rodman, K. C., T. T. Veblen, T. B. Chapman, M. T. Rother, A. P. Wion, and M. D. Redmond. 2019. Limitations to recovery following wildfire in dry forests of southern Colorado and northern New Mexico, USA. *Ecological Applications*. DOI: 10.1002/eap.2001

Workshops/Webinars for Managers

- Gambel Oak Management and Ecology. 2018. Online webinar co-organized with the Southern Rockies Fire Science Network and Utah State University. Available at: <<https://www.youtube.com/watch?v=UeEi9PWnEEo>> and <<https://www.youtube.com/watch?v=niNF9CBORCA>>

Planned

Datasets

Rodman, K. C., T. T. Veblen, T. B. Chapman, M. T. Rother, A. P. Wion, and M. D. Redmond. 2021. Data from: Limitations to recovery following wildfire in dry forests of southern Colorado and northern New Mexico, USA. Dryad Digital Repository. DOI: 10.5061/dryad.t02nd5m

The above dataset has already been archived and metadata has been submitted to JFSP and to the USDA Forest Service Research Data Archive. Data will be made available in September 2021 following a two-year embargo period. We have already given spatial datasets to local land managers, and will transfer these data to the FVS support office as planned.

Decision Support Tool for Managers

As a part of Rodman et al. (*In Prep*; listed below), we are developing an ArcGIS toolbox that aids in reforestation planning by identifying areas climatically suitable for ponderosa pine and/or Douglas-fir (using developed datasets) and without surviving overstory trees (using fire severity layers). Expected completion in summer 2020.

Peer-Reviewed Publications

Rodman, K. C., Battaglia, M. A., Coop, J. D., Fornwalt, P. J., Ouzts, J. R., & T. T. Veblen. *In Preparation*. Post-fire reforestation in a warming world: A decision optimization framework for the southern Rocky Mountains.

Rodman, K. C., Battaglia, M. A., Chambers, M. E., Fornwalt, P. J., Holden, Z. A., Kolb, T. E., Rother, M. T., Ouzts, J. R. & T. T. Veblen. *In Review*. A Changing Climate is Snuffing Out Post-Fire Recovery in Montane Forests.

APPENDIX C: METADATA

New field data collection, statistical analyses, and spatial data analyses involved in this project led to the development of several new datasets. These datasets include the following:

- 1) Seed Cone Production Data – data on seed cone production for ponderosa pine (154 individual trees) across 27 stands within 8 individual wildfires in southern Colorado and northern New Mexico. The data are aggregated to the level of individual fires and were reconstructed for the years 2003-2017. We used the cone abscission scar method (*sensu* Redmond et al. 2016) to quantify past seed cone production.
- 2) Seedling Establishment Data – data on the timing of post-fire seedling (ponderosa pine, Douglas-fir, and lodgepole pine) and sprout (Gambel oak and quaking aspen) establishment derived from tree-ring analyses of 701 destructive samples of five tree species throughout the 15 surveyed wildfires. For conifer seedlings, we identified establishment year of each sample by collecting multiple cross-sections above and below ground-level, and identifying and dating the root-shoot boundary (*sensu* Rother and Veblen 2017). We collected up to two destructive samples from each “regeneration plot” (see description below).
- 3) Regeneration Plot Data – we collected data on pre- and post-fire forest structure and post-fire seedling abundance from 555 field plots throughout 15 different wildfires in southern Colorado and northern New Mexico. Plots were established using a nested transect design with 8-12 transects per fire, and 4-6 plots located at c. 60 m intervals along each transect. Within each plots, we used variable-sized subplots to survey seedling densities. We also collected data describing post-fire groundcover in four 1 m² quadrats within each field plot.
- 4) Spatial Data – spatial datasets used to quantify expected post-fire recovery of ponderosa pine and Douglas-fir throughout each of the 15 surveyed wildfires. We include image classifications (derived from National Agriculture Imagery Program), outputs of monthly water balance models (annual average actual evapotranspiration and climatic water deficit for the 30-year period of 1981-2010), and spatially-explicit predictions of seedling densities for ponderosa pine and Douglas-fir throughout each fire perimeter.

All data have been archived in the Dryad Digital Repository, and will be made publicly available following a two-year embargo period (Rodman et al. 2021). Metadata have been submitted to the Joint Fire Science Program and are published online in the Forest Service Research Data Archive <<https://www.fs.usda.gov/rds/archive/catalog/RDS-ext-2021-0001>>.

Dataset Title: Data from: Limitations to recovery following wildfire in dry forests of southern Colorado and northern New Mexico, USA

Abstract: This dataset includes information on post-fire seed cone production, seedling establishment, seedling densities, and layers used in spatially-explicit predictions of post-fire forest recovery throughout 15 wildfires in southern Colorado and northern New Mexico, USA. All fires were selected from the Monitoring Trends in Burn Severity (MTBS) database using the following criteria: 1) vegetation type – fires must have occurred in areas with dominant components of pine-oak, ponderosa pine, or dry mixed-conifer vegetation types, 2) accessibility – fires must have occurred on accessible public land, or on large private parcels for which we

were permitted access, and 3) fires must have had only minimal areas of overlap with other fire perimeters (i.e., “reburns”). Approximately 40 post-fire regeneration plots were established throughout each fire (n = 555). Within each plot, we recorded species-specific counts of post-fire seedling density, characterized pre- and post-fire forest structure, and quantified post-fire groundcover. Within each plot, we also collected up to two destructively sampled seedlings/stems of ponderosa pine, Douglas-fir, lodgepole pine, Gambel oak, and/or aspen (n = 701). We identified the establishment year of conifers by dating the root-shoot boundary of each seedling and the establishment year of resprouting angiosperm trees by dating the innermost ring near ground level. We also dated cone production of ponderosa pine in areas adjacent to fire perimeters or in low-severity areas within fire perimeters. To reconstruct seed cone production, we used counts of cone abscission scars in 5-6 branches on 154 trees spanning 27 sites throughout eight fires. These fires were selected to span the geographic and climatic range of our sites. Seed cone production data were aggregated to average annual production at the fire-level. We also used post-fire regeneration plot data and geospatial datasets (i.e., 1-meter aerial imagery and gridded climate data) to predict post-fire seedling density throughout each fire perimeter. These field-derived and spatial datasets, associated with Rodman et al. (2019), were part of the Joint Fire Science Project ID #: 17-2-01-4.

Purpose: Limited recovery has been noted following many recent wildfires in ponderosa pine-dominated forests throughout the western USA. We collected these data in an effort to quantify several potential drivers of limited recovery, including seed production, climatic limitations to seedling establishment, as well as tree survival and spatial variation in climate throughout each fire.